SPAWAR
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San Diego

TECHNICAL REPORT 1864
June 2001

# Monitoring Moment-to-Moment Operator Workload Using Task Load and System-State Information

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## ADMINISTRATIVE INFORMATION

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# EXECUTIVE SUMMARY

Assessing and understanding operator workload is an important factor for consideration during the development of new systems. It may also be important to understand fluctuations in workload within operational systems in order to efficiently apply automated processes and provide assistance at critical times. This paper describes how a simple workload measure obtained every 2-3 minutes during the evaluation of a prototype command and control console can be used to develop an operator's workload profile as a function of other system parameters, such as track density on the tactical plot, and task loading. If system measures can be monitored regularly, functional models of operator workload can be derived, and workload levels can be interpolated to provide near-continuous workload estimates every 15-30 seconds. The resulting workload profiles can be used to identify conditions that result in potential operator overload. Profiles from several operators may be used to study team workload distribution and to derive more efficient work allocation strategies.

Also discussed in the present work is how the simple unidimensional workload measure relates to multidimensional measures that differentiate between mental demand, physical demand, frustration, and other aspects of work. Multidimensional measures require more extensive reporting and are thus not suitable for administration during system testing. A common multidimensional scale, the NASA Task Load Index (TLX), was administered at the conclusion of the each evaluation session. Regression analysis revealed that the 90th percentile from the distribution of unidimensional workload estimates related to the NASA-TLX dimensions of mental effort and temporal demand in a group of 20 operators.

These findings indicate that near-continuous workload profiles may be built from simple subjective workload estimates combined with system-state information, and that the workload estimates can be linked to specific behavioral dimensions as captured by more complex workload assessment scales.

# CONTENTS



## Figures



## Tables

# INTRODUCTION

The confluence of increased computing power, pressure to increase productivity, and efforts to reduce costs associated with human oversight within process control, manufacturing, and command and control systems promises a greater role for automation in the future. Currently, there is an emphasis on maintaining or even reducing manning levels within new systems. It is quite evident that future operators will be required to supervise automated processes and work with automation in a manner not seen previously.

Automation has been of interest to system developers for many years, and studies have generally shown that while system performance can generally be improved, performance may worsen under certain conditions. Failure of automation occurs most readily in systems that cannot be fully automated, and within which human operators must actively monitor and occasionally over-ride automated processes. Automation within dynamic settings can increase the workload of operators because of the extensive dialog with automated processes necessary to ensure proper functioning. Operator reliance on automation can result in a loss of situational awareness and complacency; this is problematical within systems requiring occasional operator control. Finally, operators may experience a loss of expertise as direct involvement in system control declines.

Previous research has established that truly adaptive systems will require information on the human operator's workload levels in real time (e.g., Byrne & Parasuraman, 1996). Parasuraman et al. (1992) have proposed that a combination of three assessment domains (environmental, activity, operator state) can provide estimates of workload with greater stability than any subset of measures. Environment or system-state information refers to knowledge of an operator's task loading. For example, the number of aircraft that must be monitored by an air traffic controller may provide a general indication of workload. Communication activity (monitored on a radio circuit) might reflect the extent to which a set of aircraft requires attention by the controller. Psychophysiological measures, (e.g., heart rate variability, electroencephalograph [EEG] spectral measures) provide insight regarding an operator's psychophysiological state, which in turn may correlate with workload (Kramer, Trejo & Humphrey, 1996; Van Orden, Jung & Makeig, 2000; Van Orden, et al. 2001).

While recent studies have suggested that psychophysiological and behavioral models are useful for determining operator state to some degree, current findings from our laboratory indicated that greater fidelity in the estimation of workload may be achieved from more precise modeling of the operator's task environment. During the course of developing a prototype command and control console for air defense warfare (ADW), Osga et al. (2001) focused on a Task-Centric Design (TCD) approach to meet the simultaneous requirements of reduced system manning and improved mission effectiveness. This design approach enabled moment-to-moment tracking of tasks to be performed by an operator. TCD was born from the realization that in order to reduce workload and assist the operator, the system must contain some knowledge of what the operator is attempting to accomplish. Hoc (2000) explains this in terms of a common frame of reference (COFOR) between the operator and machine. System "awareness" of task state and operator intent enables organization of task-supportive information, and development of tools to assist the operator in a manner that is specifically task supportive. For ADW, TCD required continuous assessment of track data to trigger tasks, the development of information sets to support those tasks, and the preparation of task products (outgoing reports, recommended tactical actions) for review by the operator. The goal in TCD is to support the operator through all task phases, from initiation to transition to new tasks. A central design feature is a task manager algorithm and display, which presents icons to the operator based

upon the system's assessment of changes within the tactical database that require response or action (see Osga et al., 2001).

System initiation and recording of task information proved to be highly valuable for moment-to-moment estimation of operator workload. ADW requires that tasks be responded to rapidly after they have been instantiated, reducing the likelihood that tasks will not be attended to for prolonged periods. The ADW tasks, as structured and supported by information sets, are relatively straightforward in terms of actions and generally require confirmation by the operator to issue messages, query tracks of interest, and order air assets to inspect suspicious radar contacts.

In Experiment 1, our goal was to determine the extent to which workload could be monitored using the frequency of tasks posted to the task manager display and the local track density of the tactical display. It was expected that real-time monitoring of tasks as they appeared on the task manager display would enable more precise real-time monitoring of operator workload. A simple unidimensional workload estimation technique was employed, allowing non-obtrusive estimation by operators throughout a 30-min air defense scenario. This unidimensional estimate was strongly associated with tactical plot track density and the frequency of tasks identified by the system. In Experiment 2, the relationship of the unidimensional workload measure to a summary multidimensional measure (NASA-Task Load Index [TLX]) was examined. Methodological and theoretical issues as they relate to the application of automation within cooperative human–machine systems are subsequently discussed.

# EXPERIMENT 1

## METHODS

*Participants*: Eight subjects, affiliated with local commands, volunteered to complete a 30-min ADW task. All were generally familiar with ADW concepts and operator activities.

*Apparatus and Procedure*: The experiment was run on a personal computer interfaced with two flat-panel color displays. The displays were arranged vertically with a tactical plot and associated information windows regarding tactical vehicles in the upper display, and a "task manager" display (Figure 1) located below. Subjects could interact with either display using touch or with a trackball.

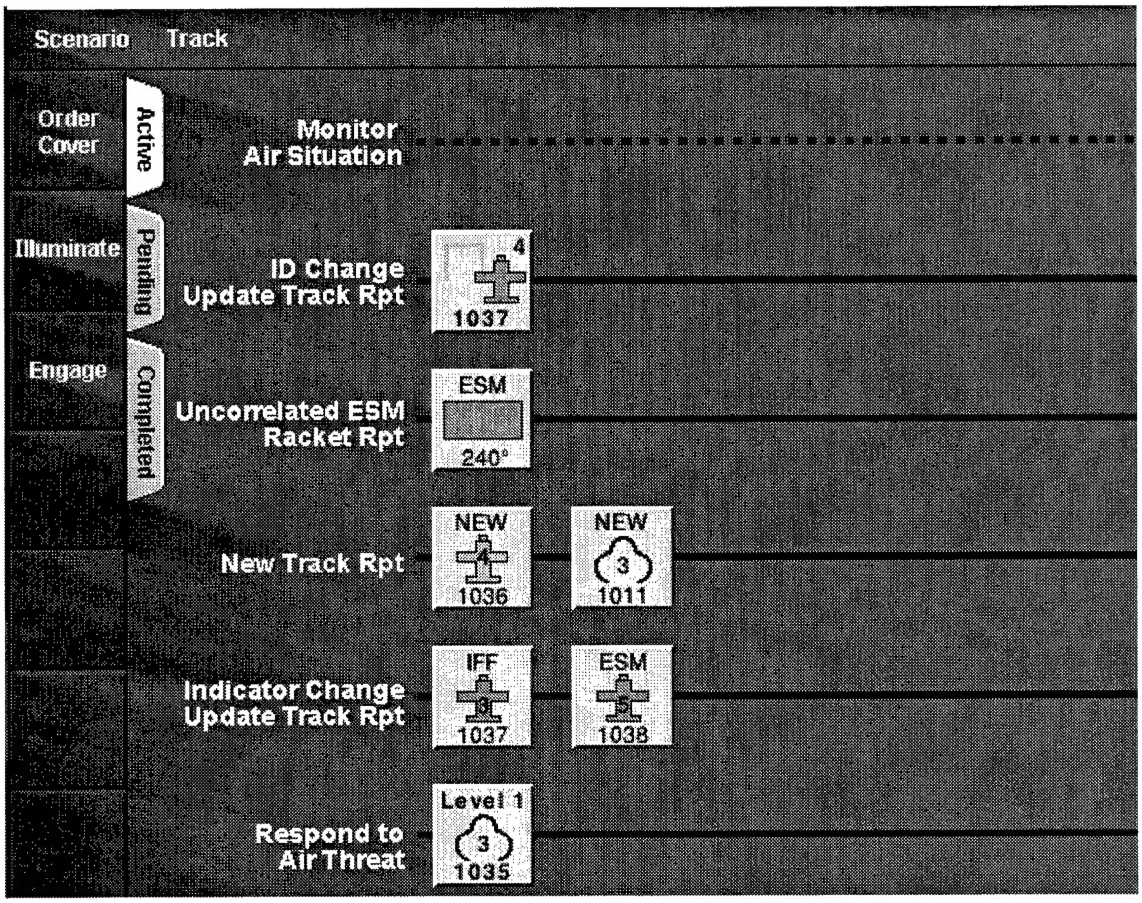


Figure 1. Task Manager display used in the experiments. Each icon represents a task, which was triggered by the system.

During a 30-min air defense scenario, subjects were required to respond to system-initiated tasks (appearing as icons in the Task Manager display) concerning reports to be generated on the occurrence of new tracks, track identification changes, and uncorrelated electronic surveillance measures (ESM) activity. Initiating a task would highlight the pertinent track on the tactical plot, present the track's summary information within summary information set windows, and produce a product (e.g., outgoing message, tactical action to be ordered) for review. Subjects were also required to observe the tactical plot and initiate level 1 queries ("who are you" questions) and level 2 warnings ("turn

away" statements) to unknown and suspect aircraft that crossed predetermined standoff distances from their ship. Standoff ranges were determined by range rings surrounding the ship and by graphics depicting the boundary between territorial and international waters. Subjects were required to enter a simple workload estimate (7-point scale) every 2 minutes (see Figure 2). Roscoe (1987) has successfully used a similar method of eliciting subjective workload estimates from pilots involved with dynamic flight activity with little task interruption. His work was based upon a scale developed by Cooper and Harper (1969) for evaluation of pilots' perception of aircraft handling characteristics. Denominations on these earlier 10-point scales were tied to a semantic decision tree regarding "tolerability" and "spare capacity" of perceived workload during the task. Roscoe concluded that the resulting output of the instrument was nonlinear with respect to task load. The 7-point scale used in the present study was anchored only by the descriptors shown in Figure 2. No nonlinearities were observed in the present data.

The general uniformity among the tasks we studied allowed them to be considered as equivalent units of work; there was no need to apply distinct visual, auditory, cognitive, and psychomotor workload estimates (see McCracken and Aldrich, 1984) to each task in order to conduct workload modeling studies. The queries and warnings tasks were initiated by the subjects and scored as three units of task work given the degree of track monitoring necessary to complete these tasks.

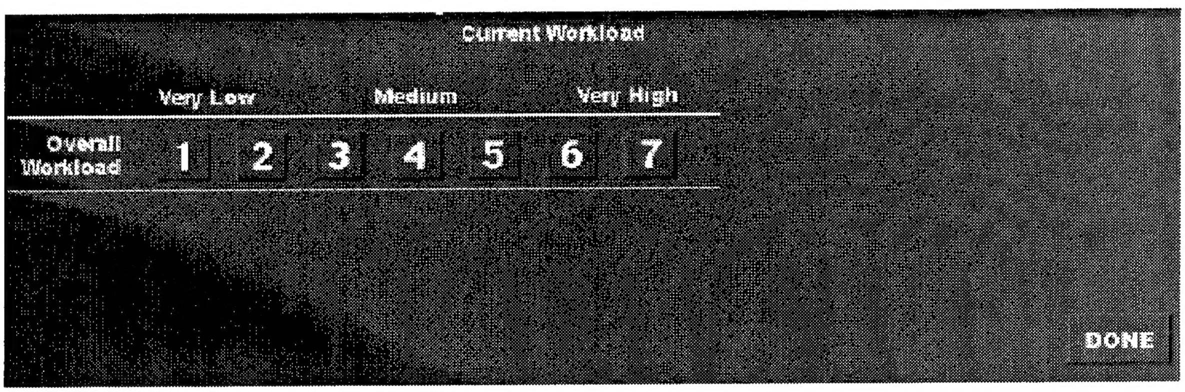


Figure 2. Subjective workload estimation prompt that appeared on the subject's display every 2 minutes during the 30-min scenario.

## RESULTS AND DISCUSSION

Figure 3 presents the target density data for the 30-min period of the scenario. These data are equivalent for each subject. Figure 4 presents the mean task loading data, obtained every 15 sec, for the eight subjects. Also plotted are the mean subjective workload estimates. While generally similar between subjects, task load data could vary as a function of how rapidly operators completed tasks.

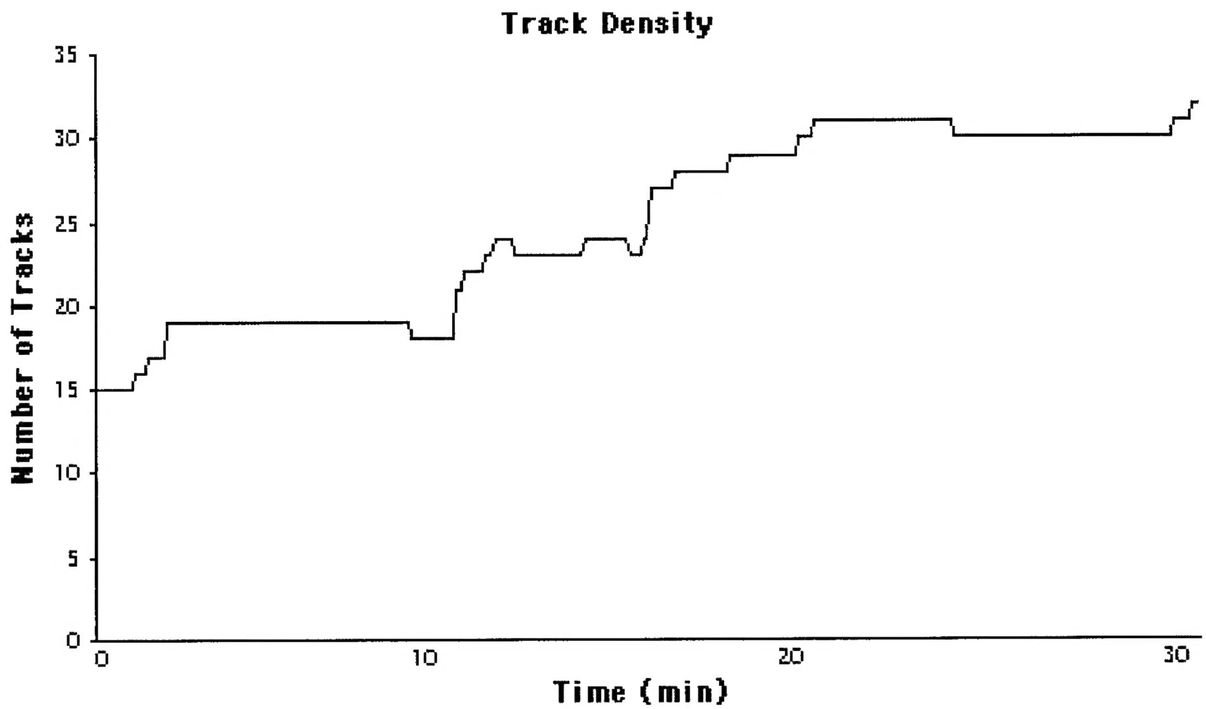


Figure 3. Track density on the tactical plot during the 30-min scenario.

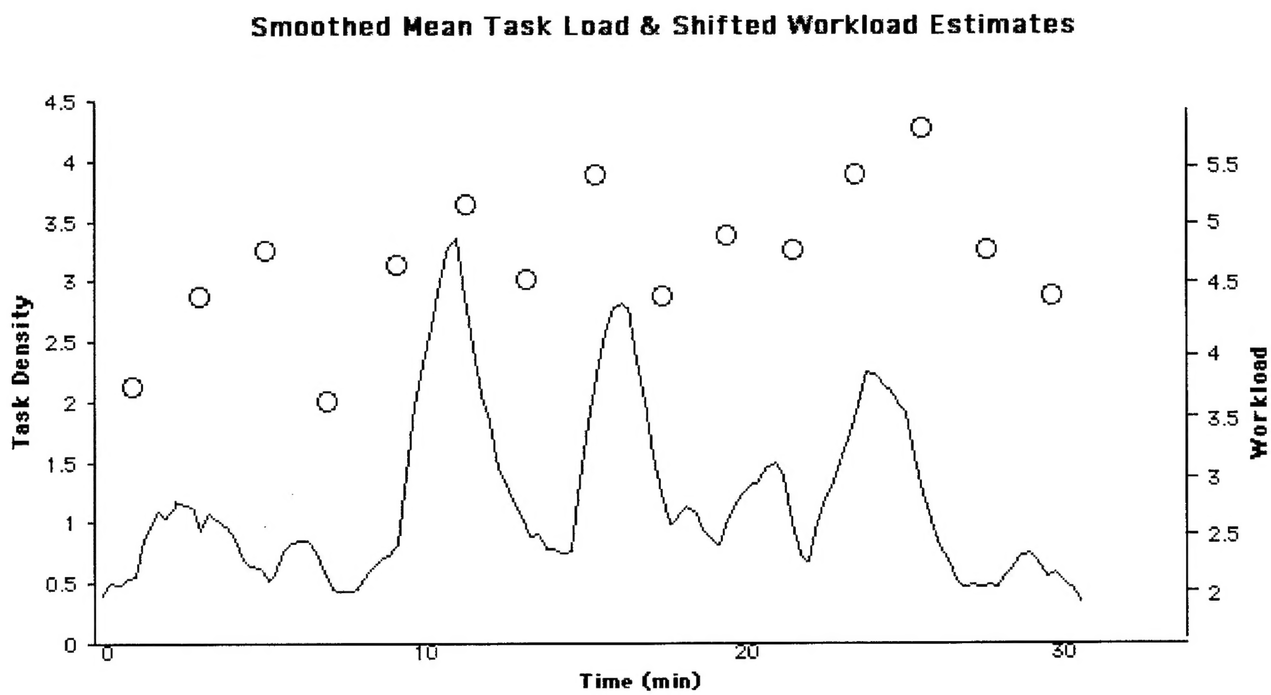


Figure 4. Mean task load (left axis, solid line) and mean subjective workload (right axis, open circles) as a function of time (in sec) for the eight subjects. Mean task load was obtained every 15 sec. Mean subjective estimates were forward-lagged by 60 sec.

A regression analysis was conducted using the target density and mean task load data to predict mean workload estimation data. This analysis indicated that for all subjects, mean task load and track density accounted for a significant portion of the variance (57 percent) in estimated workload, $F(2,12) = 8.12, p < .01, R = 0.76$. The general model was:

$$\text{Wkld} = 0.45 * \text{Task Load} + 0.05 * \text{Target Density} + 1.32$$

For the general model, task load (TL) accounted for 39 percent of the variance, while target density (TD) accounted for 19 percent.

Individual models were constructed for each subject; their parameters are presented in Table 1. These models accounted for a statistically significant portion of estimated workload variance for six of eight subjects, and demonstrated considerable variability in component weighting factors. Individual and the general models based on 15 subjective estimates could then be used to interpolate workload at 15-sec intervals for the duration of the scenario—as would be desired in a functional real-time system.

Table 1. Individual models.

| Subject | TL | TD | Intercept | R |
|---|---|---|---|---|
| S1 | .29* | .09* | .40 | .76* |
| S2 | .21 | .12* | -.94 | .71* |
| S3 | .82* | .08 | .66 | .68* |
| S4 | .42 | -.14 | 7.78 | .60 |
| S5 | .58* | .03 | 1.26 | .73* |
| S6 | -.09 | .16* | .12 | .78* |
| S7 | -.02 | .08* | -.06 | .57 |
| S8 | 1.18* | .003 | 2.06 | .69* |
| GenMod: | .45* | .05* | 1.32 | .76* |

* indicates significance at $p < 0.05$

Figure 5 presents moment-to-moment workload data derived from the general and individual models for Subject 1. As shown, the general and individual models produced similar workload profiles for this subject. Figure 6 presents similar output data, along with the original subjective workload estimates, for Subject 2. The difference between the workload profiles produced by the general and individual models are considerable for this subject, and raises some important questions. For example, is this subject truly different from the group—and does the subject have the excess workload capacity indicated by the individual model? Or is his estimation scale biased towards using low numbers compared to other subjects? In this case, the excess capacity for additional work might evaporate rapidly when this subject is challenged with additional tasks. Roscoe (1987) noted that individual variability in subjective ratings was common while using a similar instrument. The key to addressing this issue is repeated testing under conditions that drive the subjects into an overload state. Unfortunately, limited test scenario resources prevented repeated testing in this experiment.

Subject 1

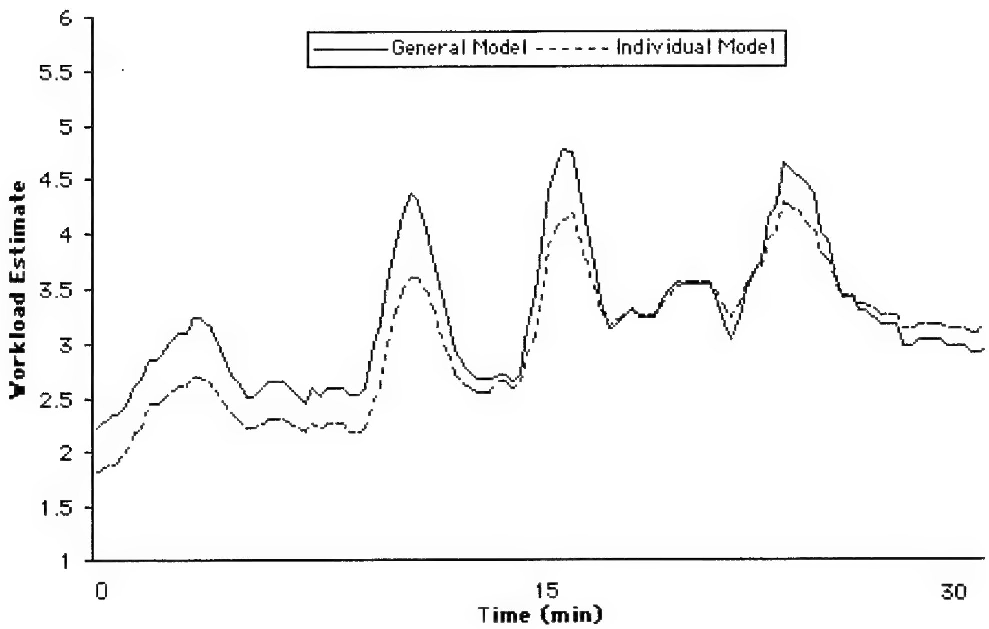


Figure 5. Workload estimates produced every 15 sec by the general and individual regression models developed from the 15 subjective workload estimation points.

Subject 2

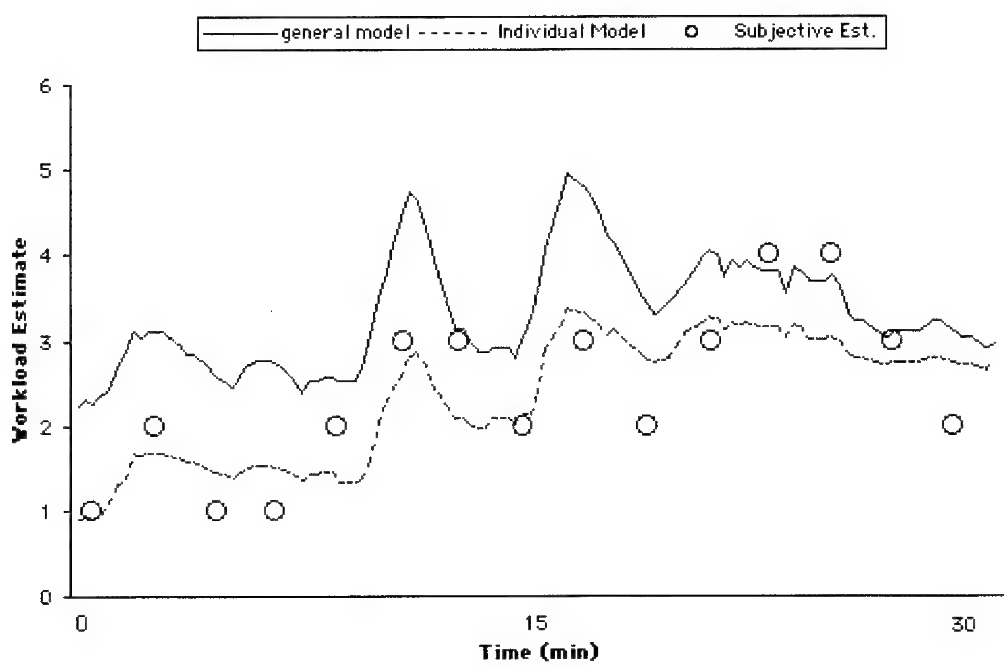


Figure 6. Moment-to-moment estimated workload data for Subject 2 based upon the general model and an individually tailored model. Original workload estimates provided by the subject during the scenario are shown as open circles.

## EXPERIMENT 2

The moment-to-moment workload measure used in the present series of studies was useful in identifying transient workload peaks and for modeling of workload as it related to task-based environmental measures. Unidimensional workload measures have been criticized for lacking information regarding what specific aspect of work (e.g., physical work, mental effort, temporal demand) is most affected by a given system and situation, prompting wide use of multidimensional workload scales such as NASA-TLX (Hart and Staveland, 1988). Because there are many situations in which multidimensional measures cannot be administered during an ongoing scenario, it is useful to understand how the local-estimate unidimensional and summary multidimensional measures relate to each other.

During the course of usability testing of our prototype command and control console, moment-to-moment and summary NASA-TLX data were obtained from 20 subjects. Time constraints did not permit the establishment of the relative TLX subscale weighting factors as originally prescribed by Hart and Staveland (used for establishing a single weighted score from pairwise comparisons of the six subscales by every subject). However, it is common practice to use a simple average of the subscale measures as at least one study (Nygren, 1991) has found no advantage to using the weighted TLX score over a simple average. Experiment 2 examined the relationship between the unidimensional and multidimensional NASA-TLX measures.

### METHODS

*Participants & Procedure*: Twenty subjects voluntarily participated. They completed between 30 and 40 min of the ADW task described previously. Between 15 and 20 unidimensional workload estimation scores were obtained during the scenario, as well as the NASA-TLX measures at the conclusion of the session.

### RESULTS AND DISCUSSION

Across all subjects, the correlation between the mean TLX score and the mean moment-to-moment workload estimation measure was weak and not statistically significant ($r = 0.18$, $p > 0.05$). Inspection of the TLX subscale data and the real-time estimates prompted a more thorough examination of their relationship. Table 2 presents the correlation matrix for the 90th percentile of the moment-to-moment measures and the TLX subscale measures across the subject sample. There was considerable variability for correlations between the TLX subscales and the real-time workload estimation measures. The 90th percentile of the unidimensional measures were calculated because of the suspicion that the NASA-TLX measures would reflect the highest workload levels experienced during the session. The maximum and the mean of the unidimensional measures were found to be far less indicative as the 90th percentile measure to changes in the TLX subscale mean data.

Table 2. Correlation matrix of workload estimates and NASA-TLX subscale means.

| | 90th Perc | EFFORT | PERFORM | FRUSTRA | TEMDEM | MENDEM | PHYSDEM |
|---|---|---|---|---|---|---|---|
| 90th Perc | 1.00 | 0.58 | -0.27 | -0.02 | 0.49 | 0.45 | 0.17 |
| EFFORT | | 1.00 | -0.17 | -0.12 | 0.39 | 0.46 | 0.71 |
| PERFORM | | | 1.00 | -0.08 | -0.20 | -0.18 | -0.20 |
| FRUSTRA | | | | 1.00 | 0.21 | 0.18 | -0.13 |
| TEMDEM | | | | | 1.00 | 0.32 | 0.39 |
| MENDEM | | | | | | 1.00 | 0.27 |
| PHYSDEM | | | | | | | 1.00 |

PERFORM, performance; FRUSTRA, frustration; TEMDEM, temporal demand; MENDEM, mental demand; PHYSDEM, physical demand

The correlation between the TLX subscales of mental effort and physical demand ($r = 0.71$) approached a multicolinearity condition (in which predictor variables are highly correlate with each other) and proved troublesome during initial regression analyses. The physical demand subscale data was excluded from further analyses, as is often necessary in such cases in order to derive robust and generalizable models (Berry and Feldman, 1985). A forward-stepwise regression procedure was used to estimate the 90th percentile workload estimation data from the remaining TLX subscale means for the 20 subjects. The procedure yielded a significant model ($F(2, 17) = 6.20$, $p < 0.01$; $R = 0.65$) containing the TLX subscale means of mental effort load and temporal demand load. The model accounted for 42 percent of the variance in 90th percentile moment-to-moment workload estimation measures. The model is expressed as follows:

$$WKLD_{90th} = 0.11 * \text{Mental Effort} + 0.10 * \text{Temporal Demand} + 1.85$$

Essentially, this model transforms TLX subscale ratings on a 20-point scale into a unidimensional 90th percentile estimate of workload on a 7-point scale. Mental effort and temporal demand accounted for 34 and 8 percent of the variance, respectively. Increases in mental effort as a function of overall workload were likely due to decisions regarding which tasks to ignore versus execute as task load increased. These data indicate that automation might be useful in assisting operators during peak task load periods.

The relationship between moment-to-moment workload estimates and TLX subscale measures described above enables some estimation of which aspects of work are changing within a situation monitored with a unidimensional measure. The relationship also raises questions about the simple averaging of TLX subscales to form a summary workload measure. Such an approach may have been appropriate within Nygren's (1991) experimental paradigm; however, data within Table 2 might indicate that simple averaging is not appropriate within the present application. It is quite possible that TLX subscales and weightings would vary between legacy and prototype command and control interfaces, as they would likely differ with respect to decision support features such as task management and other track history tools. Thus, care must be exercised when interpreting TLX means and subscale data. Modeling to unidimensional measures, as conducted in the present study, is necessary if moment-to-moment measures are used and different conditions are evaluated.

## SUMMARY

The present findings indicate that task-centric design principles and task management human–computer interface (HCI), in combination with other task load data (such as track density), provide useful information that correlates strongly to operator workload. Despite concerns raised by Tsang and Wilson (1997) over the limitations of unidimensional workload scales, the assessment instrument used in our study was useful and non-intrusive, enabling the development of reasonable workload models that could then be interpolated to produce moment-to-moment workload estimates. Instructions to subjects have recently been revised (requiring immediate response to the probe when it appears on the display) reducing the need to lag the estimates backwards in time from 60 to 20 seconds. A voice-input version of the estimation scale (following an auditory or visual icon) would enable use of fractional values and impart even less task interruption.

Recently, the task and track density data have been augmented with operator activity data. Simply obtaining the number of items selected by the operator within overlapping 30-sec intervals provides indication of general operator use of the console. Task load and selection activity data from one subject are presented in Figure 7. Also presented in Figure 7 are the subjective workload estimates provided by the subject during the 40-min scenario. The data demonstrate some expected patterns: High concurrent activity and task load levels were associated with higher subjective workload estimates. Lower activity and task loading levels were associated with lower workload estimates. Of greater interest was the observation that intermediate workload estimates were often provided when selection activity was high and task loading was minimal. Regression modeling indicated that target density, task loading, and selection activity accounted for 70 percent of the variance in estimated workload for this subject, $F(3,17) = 13.4$, $p < .001$; $R = 0.84$. The regression analysis indicated that each of the input variables contributed significantly to explaining variance in estimated workload.

The regression model, based upon the 20 subjective workload estimation points, was then used to interpolate estimated workload at 15-sec intervals throughout the entire 40-minute period. Figure 8 presents the estimated workload, based upon the track density, task load, and selection activity data streams, for the subject. The output does contain some noise that could be smoothed in a real-time system. The results indicate that simple measures of operator activity can contribute significantly to the estimation of workload; research continues to examine the relative contributions of various measures to the estimation of operator workload.

The simple task-weighting scheme used in the present study could easily be expanded to account for greater workload diversity between disparate tasks. It is conceivable that some tasks might require distinct weighting factors, adjustable depending upon the extent of automation support and appropriate automation dialog. A recent study by Vrendenburgh et al. (2000) used weighted tasks to derive local estimates of anesthesiologist's workload during actual anesthetic cases. Limited support from automation and a wide variety of monitoring and problem-solving tasks resulted in significant variance of task weightings in this domain.

Finally, patterns of operator activity may offer further indication of workload and operator state. In the presence of pending tasks, repeated sampling of information regarding a particular track or function might indicate elevated workload due to higher concern or confusion. In such cases, it might be possible to derive some measure of work efficiency. Similarly, sampling from a variety of tracks might indicate effort to more generally understand the tactical situation and predict future events. Workload associated with each of these activity profiles could be determined and thus improve overall workload estimation performance.

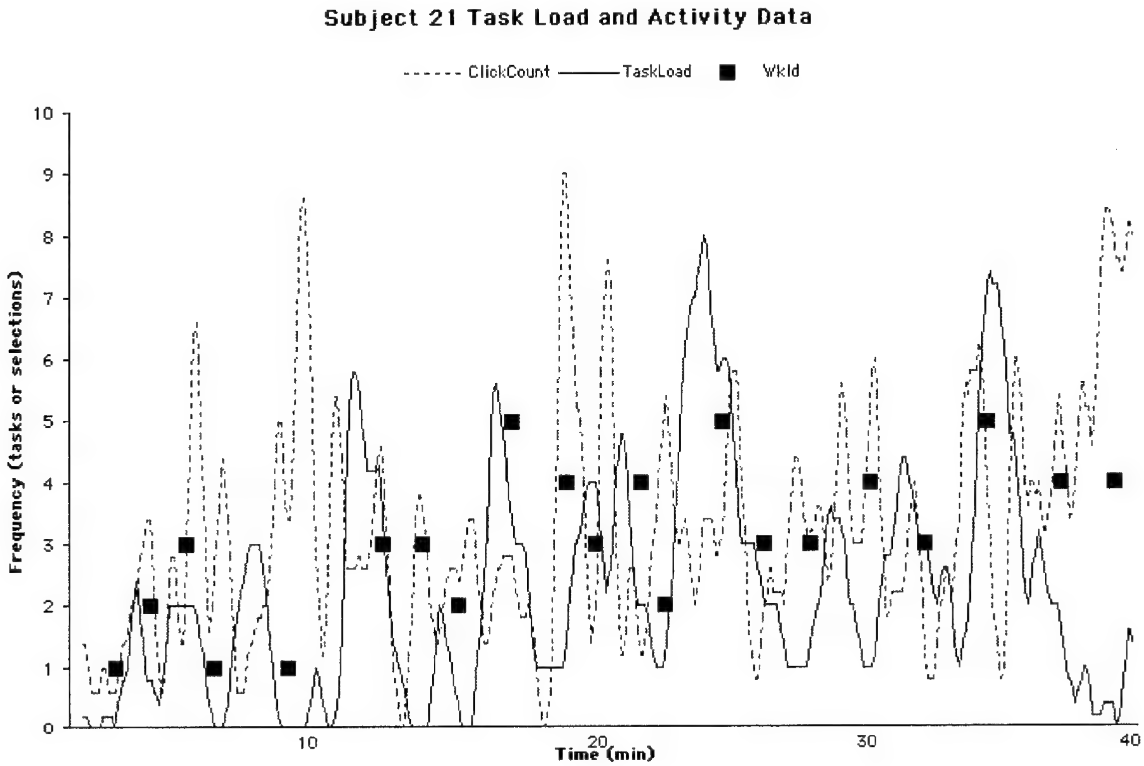


Figure 7. Task load (solid line) and selection activity (dashed line) as a function of time for one subject. Subjective estimates of workload are presented as filled squares.

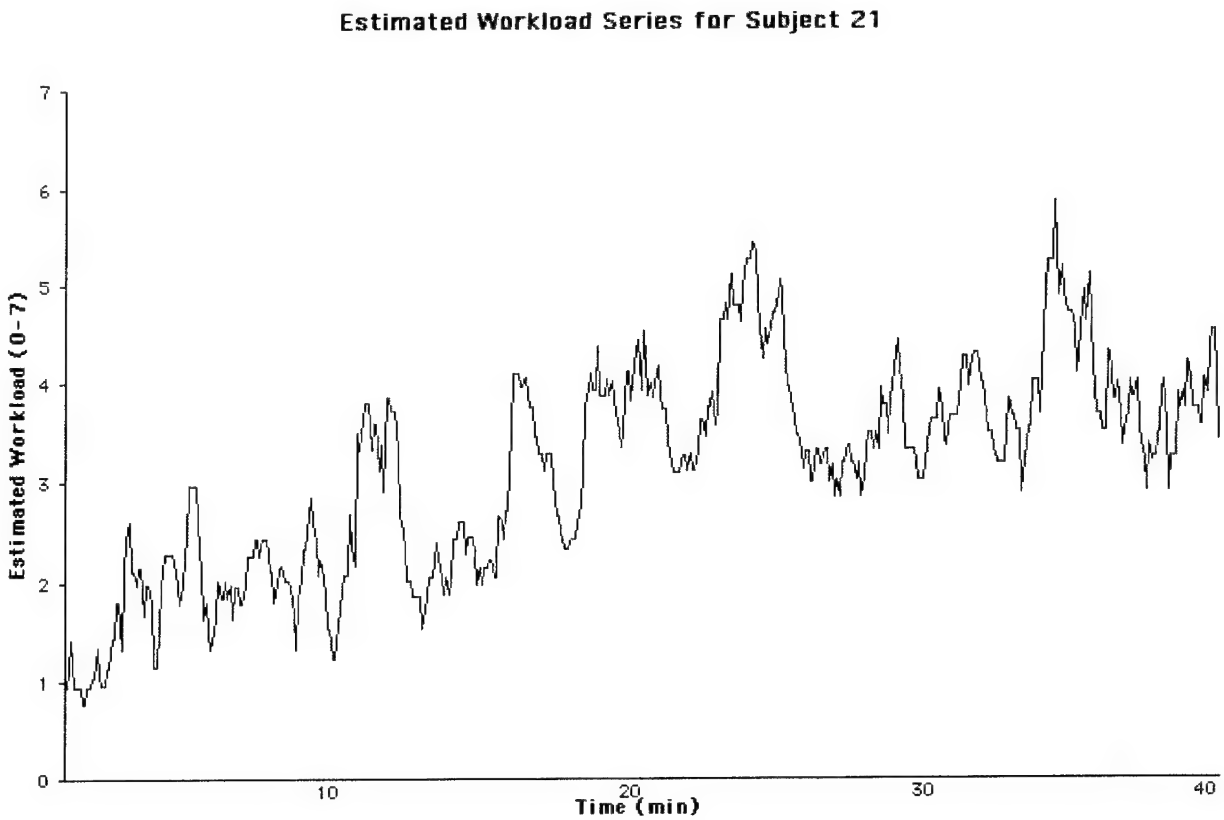


Figure 8. Regression model-generated estimated workload profile for one subject during a 40-min ADW scenario based upon continuous track density, task load, and operator activity measures.

Understanding how the interactions between the system, the operator, and the environment contribute to elevations in operator workload allows human factors engineers to more efficiently develop systems and apply automated processes. The approach used herein is useful during the prototyping stage of system development, and as a real-time method of establishing workload from multiple operators for supervisory review and for intervention by automated processes.

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**14. ABSTRACT**
Assessing and understanding operator workload is an important factor for consideration during the development of new systems. It may also be important to understand fluctuations in workload within operational systems in order to efficiently apply automated processes and provide assistance at critical times. This paper describes how a simple workload measure obtained every 2 to 3 minutes during the evaluation of a prototype command and control console can be used to develop an operator's workload profile as a function of other system parameters, such as track density on the tactical plot, and task loading.

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